NCAA March Madness Predictions

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from pandas_datareader import data
import numpy as np
from statistics import mean

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV

%matplotlib inline
```

The dataset shown below is a mix of ESPN and Ken Pom's basketball statistics. Quite a bit of work has already been done to clean and merge the data, as well as find the best predictors. Using this data, I will try to identify the optimal statistical method to predict the outcome of future games.

In [2]:
```
NCAA = pd.read_csv(r"C:/Users/ia767/Documents/NCAA_big.csv")
```

In [3]:
```
NCAA.head()
```

Out[3]:

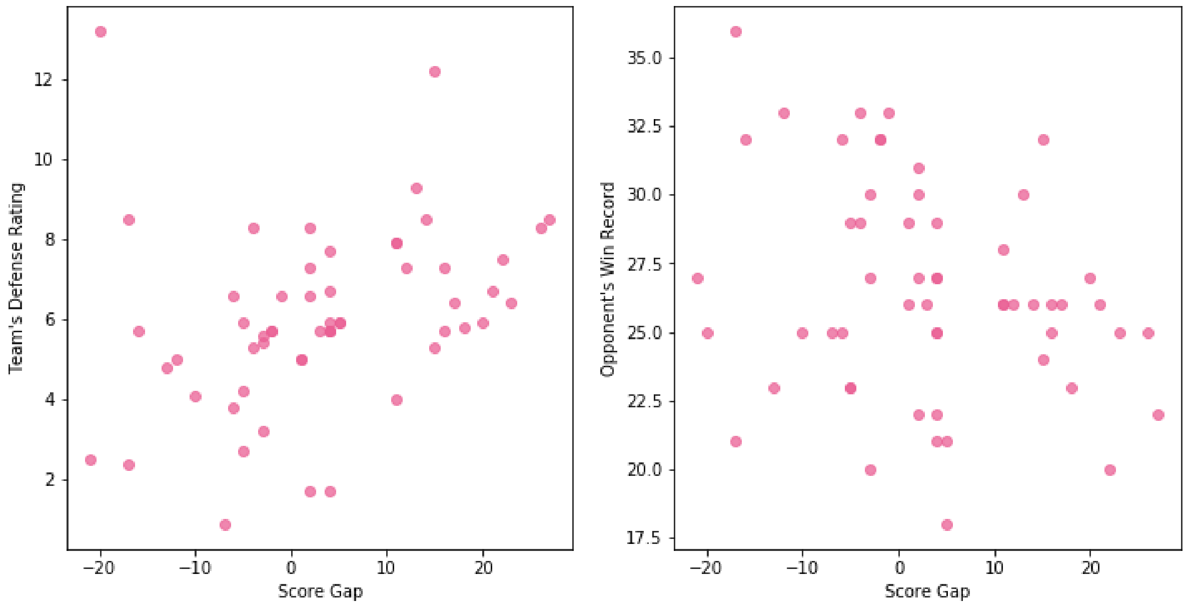
	Unnamed: 0	Team_1	Team_2	Score_Gap	Win	RK_1	BPI_1	BPI_OFF_1	BPI_DEF_1
0	1	Virginia	UMBC	-20	0	2	20.2	7.0	13.2
1	2	Creighton	Kansas State	-10	0	24	12.2	8.1	4.1
2	3	Kentucky	Davidson	5	1	19	12.9	7.0	5.9
3	4	Arizona	Buffalo	-21	0	26	11.9	9.4	2.5
4	5	UMBC	Kansas State	-7	0	156	0.7	-0.2	0.9

5 rows × 61 columns

The two variables below were selected elsewhere using forward subset selection.

In [4]:
```
y = NCAA['Win']
X = NCAA[["BPI_DEF_1", "Wins_2"]]
```

In [5]:
```
fig, ax = plt.subplots(1, 2, figsize = (12, 6))
ax[0].scatter(NCAA['Score_Gap'], NCAA["BPI_DEF_1"], color = "#ea5f94", alpha =
0.75)
ax[1].scatter(NCAA['Score_Gap'], NCAA["Wins_2"], color = "#ea5f94", alpha = 0.
75)
ax[0].set_xlabel("Score Gap")
ax[0].set_ylabel("Team's Defense Rating")
ax[1].set_xlabel("Score Gap")
ax[1].set_ylabel("Opponent's Win Record")
plt.show()
```



Model Selection

The first model I run is Logistic Regression.

In [6]:
```
logreg = LogisticRegression().fit(X, y) #using default C
print("Test set score: {:.2f}".format(logreg.score(X, y)))
print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(logreg, X, y, cv
=10))) )
```

```
Test set score: 0.73
CV Test Score: 0.72
```

In [7]:
```
from sklearn import preprocessing
```

In [8]:
```
scaler = preprocessing.StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

In [9]:
```
logreg_scaled = LogisticRegression().fit(X_scaled, y) #using default C
print("Test set score: {:.2f}".format(logreg_scaled.score(X_scaled, y)))
print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(logreg_scaled, X
_scaled, y, cv=10))) )
```

```
Test set score: 0.70
CV Test Score: 0.71
```

In [10]:
```
param_grid = {'C': np.arange(0.1, 100, 5)} #goes from >0 to 100 (since 100 was
baseline)

grid = GridSearchCV(LogisticRegression(), param_grid=param_grid, cv=10)

grid.fit(X, y) #finding best C

best_C = grid.best_params_["C"] #storing best C

logreg_bestC = LogisticRegression(C = best_C).fit(X, y) #using optimal C

print("Test set score: {:.2f}".format(logreg_bestC.score(X, y)))
print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(logreg_bestC, X,
y, cv=10))) )
```

```
Test set score: 0.75
CV Test Score: 0.72
```

The base logit model has as good a CV test score as any of its 'optimized' iterations.

The next model I try is K-Nearest Neighbors, using grid search to find the optimal value of K.

In [11]:
```
param_grid = {'n_neighbors': np.arange(1, 30, 2)}
grid = GridSearchCV(KNeighborsClassifier(), param_grid=param_grid, cv=10)
grid.fit(X, y)

best_k = grid.best_params_["n_neighbors"] #storing best K

knn = KNeighborsClassifier(n_neighbors = best_k).fit(X, y)

print("best mean cross-validation score: {:.3f}".format(grid.best_score_))
print("best parameters: {}".format(grid.best_params_))
print("Test set score: {:.3f}".format(grid.score(X, y)))
print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(knn, X, y, cv=10
))) )
```

```
best mean cross-validation score: 0.768
best parameters: {'n_neighbors': 7}
Test set score: 0.857
CV Test Score: 0.77
```

The optimized KNN model improves on the Logit's test score by 5%.

I now turn to tree models, starting with a simple Decision Tree Classifier.

In [12]:
```
from sklearn.tree import DecisionTreeClassifier

tree_basic = DecisionTreeClassifier().fit(X, y)

print("Test set score: {:.3f}".format(tree_basic.score(X, y)))
print("CV Test Score: {:.2f}".format(np.mean(cross_val_score(tree_basic, X, y,
cv=10))) )
```

```
Test set score: 1.000
CV Test Score: 0.69
```

In [13]:
```
from sklearn.ensemble import RandomForestClassifier

tree_rfc = RandomForestClassifier(n_estimators=200).fit(X, y)

print("Test set score: {:.3f}".format(tree_rfc.score(X, y)))
print("CV Test Score: {:.2f}".format(np.mean(cross_val_score(tree_rfc, X, y, c
v=10))) )
```

```
Test set score: 1.000
CV Test Score: 0.75
```

In [14]:
```
from sklearn.ensemble import BaggingClassifier

tree = DecisionTreeClassifier() #Need to instantiate a model type for bagging
 first
tree_bag = BaggingClassifier(tree, n_estimators=100,
                        random_state=1).fit(X, y)

print("Test set score: {:.3f}".format(tree_bag.score(X, y)))
print("CV Test Score: {:.2f}".format(np.mean(cross_val_score(tree_bag, X, y, c
v=10))) )
```

```
Test set score: 1.000
CV Test Score: 0.75
```

Neither of these tree models improves on the KNN's score.

I do take advantage of the tree models to look at the contribution of my independent variables.

In [15]:
```
print(tree_rfc.feature_importances_)
X.columns
```

```
[ 0.53014213  0.46985787]
```

Out[15]:
```
Index(['BPI_DEF_1', 'Wins_2'], dtype='object')
```

They seem to contribute about equally to the model's predictive power.

The final model I run is a Support Vector Machine. I first run a linear version, tuning its parameters, then a non-linear SVM. The parameter tuning of the non-linear SVM is somewhat limited because the code always runs very slowly.

```
In [16]: from sklearn.svm import SVC

         param_grid = {'C': np.arange(1, 600, 20)}
         grid = GridSearchCV(SVC(kernel = "linear"), param_grid=param_grid, cv=10)
         grid.fit(X, y)

         best_C = grid.best_params_["C"] #storing best C

         svc_linear = SVC(kernel = "linear", C = best_C).fit(X, y)

         print("best mean cross-validation score: {:.3f}".format(grid.best_score_))
         print("best parameters: {}".format(grid.best_params_))
         print("Test set score: {:.3f}".format(grid.score(X, y)))
         print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(svc_linear, X, y
         , cv=10))) )
```

```
best mean cross-validation score: 0.750
best parameters: {'C': 1}
Test set score: 0.750
CV Test Score: 0.74
```

```
In [17]: param_grid = {'C': np.arange(1, 600, 10),
                       'gamma': [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.015, 0.5]} #manua
         l bc otherwise very slow
         grid = GridSearchCV(SVC(kernel = "rbf", gamma = 0.001), param_grid=param_grid,
         cv=10)
         grid.fit(X, y)

         best_C = grid.best_params_["C"]

         svc = SVC(kernel = "rbf", C = best_C, gamma = 0.001).fit(X, y)

         print("best mean cross-validation score: {:.3f}".format(grid.best_score_))
         print("best parameters: {}".format(grid.best_params_))
         print("Test set score: {:.3f}".format(grid.score(X, y)))
         print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(svc, X, y, cv=10
         ))) )
```

```
best mean cross-validation score: 0.821
best parameters: {'C': 141, 'gamma': 0.015}
Test set score: 0.893
CV Test Score: 0.76
```

The problem with this approach is that the GridSearch picks the best **Test** set score. Playing around with values manually actually yields better results.

In [18]:
```
svc = SVC(kernel = "rbf", C = 600, gamma = 0.01).fit(X, y)

print("Test set score: {:.3f}".format(svc.score(X, y)))
print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(svc, X, y, cv=10
))) )
```

```
Test set score: 0.875
CV Test Score: 0.82
```

The code below optimizes the SVC based on test score instead:

In [19]:
```
scores = []

for i in np.arange(1, 600, 10):
    model = SVC(kernel = "rbf", C = i, gamma = 0.01).fit(X, y)
    cv_score = np.mean(cross_val_score(model, X, y, cv=10))
    scores.append(cv_score)

scores.index(max(scores)) #finding position of max
print("Optimal C: {}".format(np.arange(1, 600, 10)[scores.index(max(scores
))])) #finding optimal value of C
print("Best CV Test Score: {}".format(round(max(scores), 2))) #finding best sc
ore
```

```
Optimal C: 291
Best CV Test Score: 0.82
```

The optimized SVC improves on our previous best test score by 5%. It is therefore the model I keep for prediction purposes.

Prediction

The dataset below contains all of the same information as our training set, updated for 2019.

```
In [20]: NCAA_19 = pd.read_csv(r"C:/Users/ia767/Documents/NCAA_big_19.csv")
         NCAA_19.head()
```

Out[20]:

	Unnamed: 0	Team_1	Team_2	RK_1	CONF_1	W-L_1	BPI_OFF_1	BPI_DEF_1	BPI_1	D
0	1	Duke	Virginia Tech	3	ACC	31-5	10.9	10.6	21.5	--
1	2	LSU	Michigan State	20	SEC	28-6	8.5	4.4	12.9	3
2	3	Virginia	Oregon	1	ACC	31-3	11.8	11.6	23.4	--
3	4	Purdue	Tennessee	9	Big Ten	25-9	11.0	6.4	17.4	1
4	5	Florida State	Gonzaga	14	ACC	29-7	6.3	8.5	14.8	2

5 rows × 61 columns

```
In [21]: SVC(kernel = "rbf", C = 291, gamma = 0.01).fit(X, y).predict(NCAA_19[["BPI_DEF
         _1", "Wins_2"]])

Out[21]: array([1, 1, 1, 0, 0, 1, 1, 1], dtype=int64)
```

This yields my predictions for the upcoming games. The output is "1" if team 1 is predicted to win and 0 otherwise. That is: Duke will win against VT, LSU against Michigan State, etc.

```
In [22]: NCAA_19["preds"] = SVC(kernel = "rbf", C = 291, gamma = 0.01).fit(X, y).predic
         t(NCAA_19[["BPI_DEF_1", "Wins_2"]])
         NCAA_19[["Team_1", 'Team_2', "preds"]]
```

Out[22]:

	Team_1	Team_2	preds
0	Duke	Virginia Tech	1
1	LSU	Michigan State	1
2	Virginia	Oregon	1
3	Purdue	Tennessee	0
4	Florida State	Gonzaga	0
5	Texas Tech	Michigan	1
6	Houston	Kentucky	1
7	Auburn	North Carolina	1

Adding Variables

Which variables could I add to the model to improve my prediction?

I use correlation with our dependent variable as a selection criterion. I also choose variables with low correlation with my current dependent variables to make sure they will contribute to my prediction model.

```
In [23]: NCAA.corr()[["Win", "BPI_DEF_1", "Wins_2"]][(abs(NCAA.corr()["Win"]) > abs(0.2
         )) & (abs(NCAA.corr()["BPI_DEF_1"]) < abs(0.35))
                                                   & (abs(NCAA.corr()["Wins_2"]) < abs
         (0.35))]
```

Out[23]:

	Win	BPI_DEF_1	Wins_2
Unnamed: 0	0.201331	0.157051	-0.042503
Score_Gap	0.784962	0.306255	-0.259920
Win	1.000000	0.267286	-0.302102
Wins_1	0.349615	0.346597	0.037474
AdjEM_1_1_1	0.210072	0.303083	-0.142803
OppD_1	-0.228382	-0.218900	0.118188
X19_1	-0.241566	-0.272801	0.105683
Luck_2	-0.241174	0.137012	0.154525
X13_2	0.229904	-0.091662	-0.186480
AdjEM_2_2_2	0.298900	0.122751	-0.099345
X21_2	-0.287844	-0.113268	0.137406

This gives us quite a bit of choice when it comes to our new variables. The code below finds the new test CV for the selected non-linear model for every one of these variables.

The new variables I'm considering are below.

```
In [24]: NCAA.corr()[["Win", "BPI_DEF_1", "Wins_2"]][(abs(NCAA.corr()["Win"]) > abs(0.2
         )) & (abs(NCAA.corr()["BPI_DEF_1"]) < abs(0.35))
                                                   & (abs(NCAA.corr()["Wins_2"]) < abs
         (0.35))].index[4:]
```

```
Out[24]: Index(['AdjEM_1_1_1', 'OppD_1', 'X19_1', 'Luck_2', 'X13_2', 'AdjEM_2_2_2',
                'X21_2'],
               dtype='object')
```

In [25]:
```
x = NCAA.corr()[["Win", "BPI_DEF_1", "Wins_2"]][(abs(NCAA.corr()["Win"]) > abs
(0.2)) & (abs(NCAA.corr()["BPI_DEF_1"]) < abs(0.35))
                                          & (abs(NCAA.corr()["Wins_2"]) < abs
(0.35))].index[4:] #possible variables
initial = ["BPI_DEF_1", "Wins_2"]

for i in range(0, len(x)):
    initial = ["BPI_DEF_1", "Wins_2"]
    initial.append(x[i])
    X = NCAA[initial]
    svc = SVC(kernel = "rbf", C = 291, gamma = 0.01).fit(X, y)
    print(x[i])
    print("CV Test Score: {:.2f}".format( np.mean(cross_val_score(svc, X, y, c
v=10))) )
```

```
AdjEM_1_1_1
CV Test Score: 0.76
OppD_1
CV Test Score: 0.73
X19_1
CV Test Score: 0.68
Luck_2
CV Test Score: 0.80
X13_2
CV Test Score: 0.52
AdjEM_2_2_2
CV Test Score: 0.76
X21_2
CV Test Score: 0.63
```

None of these variables actually improve the model. It seems like Luck_2 is the 'best' of the batch, but it is essentially a residual (and might not carry over for another year), so I'll focus on AdjEM_1_1_1 & AdjEM_2_2_2 for now. (The model was tuned using a different set of variables, so maybe the 'optimized' performance will be better).

In [26]:
```
X = NCAA[["BPI_DEF_1", "Wins_2", "AdjEM_1_1_1"]]
scores = []

for i in np.arange(1, 600, 10):
    model = SVC(kernel = "rbf", C = i, gamma = 0.01).fit(X, y)
    cv_score = np.mean(cross_val_score(model, X, y, cv=10))
    scores.append(cv_score)

scores.index(max(scores)) #finding position of max
print("Optimal C: {}".format(np.arange(1, 600, 10)[scores.index(max(scores
))])) #finding optimal value of C
print("Best CV Test Score: {}".format(round(max(scores), 2))) #finding best sc
ore
```

```
Optimal C: 91
Best CV Test Score: 0.77
```

In [27]:
```
X = NCAA[["BPI_DEF_1", "Wins_2", "AdjEM_2_2_2"]]
scores = []

for i in np.arange(1, 600, 10):
    model = SVC(kernel = "rbf", C = i, gamma = 0.01).fit(X, y)
    cv_score = np.mean(cross_val_score(model, X, y, cv=10))
    scores.append(cv_score)

scores.index(max(scores)) #finding position of max
print("Optimal C: {}".format(np.arange(1, 600, 10)[scores.index(max(scores
))])) #finding optimal value of C
print("Best CV Test Score: {}".format(round(max(scores), 2))) #finding best sc
ore
```

```
Optimal C: 201
Best CV Test Score: 0.78
```

Neither actually improves the model.